Chapter ID 016

Theme – Anomaly and fault detection

Health and fall monitoring notifier for elderly and ill patients

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Abstract

Each year, immeasurable older people—those sixty-five and older— fall. In fact, over one out of four older individuals fall every year, one out of two however get the needed medical within time. Falls are thought-about the main reason behind concern and loss of independence among the aged population and also are a major reason behind morbidity, incapacity and health care utilization. Over 800,000 patients a year area unit hospitalized thanks to a fall related injury, most frequently thanks to a head injury or hip fracture. Therefore, it's of utmost importance that we tend to take measures to forestall falls as a result of hindrance is healthier than cure.

To tackle the given problem, we are creating a fall detection and health warning belt to detect all kinds of fall, fever and heart rate of the aged individual and warn caretakers or responsible members of the family about the fall so that medical care can be provided as soon as possible.

Keywords – fall, injury, fever, heart rate

Introduction

This elderly monitoring system can be used on the elderly wrist and has 90% accuracy in detecting hazard conditions. The system does not trigger any false alarm when used during normal activities. The system successfully displays information clearly through an Android-based application and is able to send notifications with a delay of under two seconds. This study aims to prevent the fall of people using a belt. The ability to automatically detect these fall events could help reducing the response time and significantly improve the prognosis of fall victims. The device will be fitted in a simple wearable belt making it accessible and lightweight for any age group to wear. The system aims to detect a fall and increasing pulse rate and triggers the alert system thus, alerting people around to minimize the impact of the fall. Fall will be detected through a linear prediction model algorithm with a tri-axis gyroscope and accelerometer. We will be analyzing and sending the warning message to a registered smartphone using an Arduino UNO and GSM SIM 900a. Heart condition will be detected through a pulse oximeter. Determination of fever will be based on reading of the temperature sensor.

Analytical Framework

Literature Review –

The design and development of a production prototype Balance Belt by C.Wall, III, N. D. Lyford, K. H. Sienko, M. D. Balkwill, Member, IEEE. discusses the development of a balance device from lab to clinic/home use. An emerging practice among physical therapists in balance training and falls prevention addresses a serious health problem within the United States: imbalance and its consequences. The annual cost for treating balance disorders exceeds exceeds $1 billion, not including the price to treat falls. They aim to develop a non invasive device worn round the waist. It detects when an individual is tipping too far in any direction and vibrates on that side, signalling the wearer to remain within their limits of stability. Because this new technology gets a patient to a better level of function during a shorter number of trials, it offers a chance to advance rehabilitation by enabling simpler outcomes for the same number of treatment sessions.

In Accelerometer-Based Fall Detection for Smart by Bruno Aguiar , Tiago Rocha, et al. paper they present an unobtrusive smartphone based fall detection system that uses a combination of data derived from machine learning classification applied during a state machine algorithm. the info from the smartphone built-in accelerometer is continuously screened when the phone is within the user's belt or pocket. Upon the detection of a fall event, the user location is tracked and SMS and email notifications are sent to a collection of contacts. The accuracy of the fall detection algorithm here proposed is near 97.5% for both the pocket and belt usage. lastly, the proposed solution can reliably detect fall events without disturbing the users with excessive false alarms, presenting also the advantage of not changing the user's routines, since no additional external sensors are required.

Most of the fall detection systems using mobile devices use accelerometers as the primary sensor. Accelerometry may be a useful mechanism to live the acceleration of various parts of the human body, and thus a great tool for fall detection [6], and in general for human activity recognition [7]–[10]. Threshold-based methods are one of the foremost popular techniques for fall detection using wearable sensors. Here, a fall is reported when the acceleration goes beyond a pre-defined threshold. A typical problem with this approach is that the difficulty of generalizing results for diverse populations (e.g., height and weight). Thereby, these methods need a set of predefine parameters that ought to be adjusted consistent with the target population. Research on this category include the work of De La Hoz et al. [11]. during this work the authors use the smartphones built-in sensors (accelerometer, gyroscope) to spot the location of the cell phone within the user's body (chest, pocket, holster, etc), and to find known patterns related to falls. An overall accuracy of 81.3% was reached, with top three locations to detect a fall: texting with a 95.8% fall detection accuracy, pants side pocket with an 87.5% accuracy, and shirt chests pocket with an 83.3% accuracy. Following similar approach, Kangas et al. [12] used specific locations within the user's body to compute different thresholds with data collected from a three-axes accelerometer, and gyroscope. Sensor locations with the best fall recognition accuracy included places such as the user's waist and head. Additionally, the study found that the features with significant contribution for fall recognition were the sum vector, dynamic sum vector, vertical acceleration, and maximum and minimum values. Finally, et al. [13] presents a fall detection system supported accelerometery. Here, the sensor is found within the user's pelvis.

The solution is predicated on scenarios, namely stand still, sit to stand, stand to sit, walking, walking backwards, stoop, jump and lie on the bed. Fall detection is then performed within the context of this scenarios. The following features were extracted from motion data: sum vector, magnitude of acceleration, acceleration on the horizontal plane and reference velocity. By using these feature the system was ready to infer spatial changes of the acceleration while falling. Results showed a high level of fall recognition using this treasure-based approach.

EXISTING TYPES OF FALL DETECTION:

A. Vision based approach using camera: - This technique involves putting in cameras around area of activity of the person, for example-their house. These cameras then capture images during a fall and uploads the photographs onto an in house based server, which then triggers a notification to be sent to the caretaker.[1] The disadvantage of this particular approach is that it's not portable and sometimes blurry images can be taken, which can cause further evaluation difficult. Also, if the person is inactive for an extended period of your time it considers it as a fall.

B. Machine Learning based approach: - This approach involves using machine learning algorithms such as SVM (support vector machine), k-NN (k-Nearest Neighbour), Naive Bayes, etc., to classify falls from other daily activities.[2] the info which is required to coach the model is taken from sensors like accelerometers, gyroscopes, etc. The disadvantage of this approach is that it's tons of computational requirements, thus making the value higher.

C. Vibrations and Sound-based approach: - This approach involves analysing the ground vibrations and sounds that arises from the impact between the person and therefore the floor. By analysing these parameters, the algorithm can distinguish between a true fall and other activities. These vibrations and sound are captured by an accelerometer (vibration sensor) and a microphone (sound sensor) respectively.[3] The major disadvantage of such a system is that it can cause tons of false classification and therefore the entire setup is confined to a specific space, thus causing a portability problem.

D. Kinematic based approach (ambient approach): - This approach is understood for its portability, simple use and cost effectiveness. It’s a less expensive approach to the opposite approaches and it's more portable because it is often miniaturized to be worn on the wrist.[4][5] this system uses sensors such as accelerometers, PIR sensors, etc., to analyse ad compute if a fall has occurred. It uses a more mathematical and straightforward logical algorithm to implement a fall detection system.

METHODOLOGY:

The MPU6050 accelerometer is the component that's used to detect the fall. based on the acceleration experienced along the three axes of the accelerometer (x, y, z) it produces equivalent voltages as an output. This voltage given by the accelerometer is measured by the microcontroller with the assistance of the ADC (analog-to-digital converter). These measured ADC values are then converted into its equivalent ‘g’ values (1g= 9.80665 m/s^2) using the expression: -

$$X=\frac{\frac{valx-VCC}{1024}-1.5}{0.33}\ g$$

X=Respective Value along X-axis in g’s
Valx =measured ADC value along x-axis
VCC=input voltage to the accelerometer

Once the values along all three axes are found in g, we can find the resultant value for easier further computation. The resultant is calculated using the equation: -

$$R=\sqrt{(X)^2+(Y)^2+(Z)^2}\ g$$

X=g value along x-axis
Y=g value along y-axis
Z=g value along z-axis
R=resultant g value

Now the whole algorithm to detect the fall works on the resultant gravitational acceleration. to understand how the resultant value (R), we must first understand how the gravitational acceleration values change when an individual or a body fall. When an individual is walking, siting, or doing any other normal reasonable work, the gravitational acceleration values is higher and if we discover the resultant value, it'll be more than 1g. It’ll be higher for more rigorous tasks like running, jumping, etc., and lesser for fewer rigorous tasks like waking, siting, etc., but the resultant is usually above 1g. the sole scenario where a body achieves a resultant value below 1g is during free-fall, i.e., when the body falls. A body falling from a good height essentially experiences 0g resultant, but in case of an individual falling the resultant will be a value between 0g and 1g. Upon impact with the ground the resultant to spike to a large value. So, for a fall, there's a drop in the resultant to below 1g during free fall time and so immediately an enormous spike on impact with the ground.

Algorithm 1 Fall detection algorithm

```
Initialize
while True do
  Measure Accelerometer and gyroscope
  if Acceleration > threshold then
    if Position variation > threshold then
      Wait 3 Seconds
      if Position variation > threshold then
        Wait 30 Seconds
        if !(Stop button pressed) then
          Fall detected
          Start emergency protocol
        end if
      end if
    end if
  end if
end while
```

So, this mechanism is that the core base for the algorithm employed in this paper. The algorithm continuously computes the individual axes g values from the ADC measurements and then computes the resultant (R). The algorithm continuously monitors the resultant value and sees if it goes below 1g. If it does, the algorithm immediately waits to ascertain if there a spike within the resultant values thanks to the impact with the ground. If there's a spike the algorithm identifies it as a fall and calls the GPS and GSM modules.

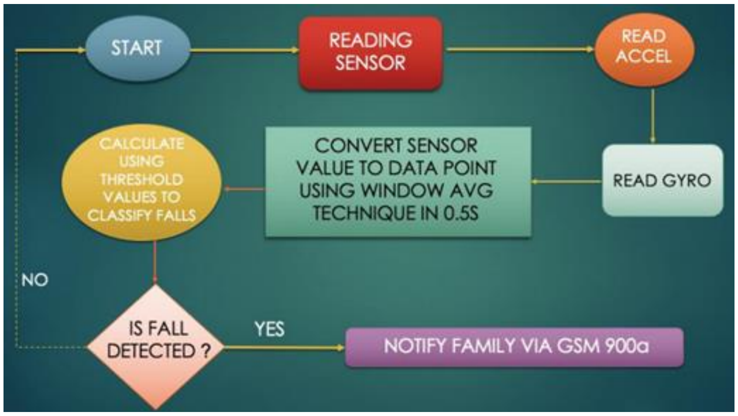

Fig1: Flowchart of Hardware

Heart rate is an important health indicator as it represents the human life status. Lower or higher heart rate shows health disorder of elderly and need to be handled as soon as possible. There are some small-sized electronic sensors available to monitor heart rate. The sensors are suitable to be used in wrist and quite capable in resulting accurate measurement. The urgency and supporting technology have driven this indicator as the suitable function of the system. We will measure pulse through pulse detector and report any anomalies through SMS.

There are two ways to measure body temperature, analog and digital. Measurement is done by putting thermometer at particular parts of body such as armpit, forehead, neck, ear, or tongue. Other parts of the body cannot generate accurate result. Besides, blood pressure also can cause difference in body and hand temperature. Hence, body temperature is not suitable as one of the functions of wearable IoT system. We will measure this parameter through TMP temperature sensor and report any anomalies as mentioned earlier.

COMPONENTS-

- Arduino UNO
- MPU 6050
- GSM SIM 900
- BSNL 3G SIM
- 16 x 2 LCD
- Push Button
- Breadboard
- Pulse detector sensor
- Battery
- Temperature Sensor

Results :-

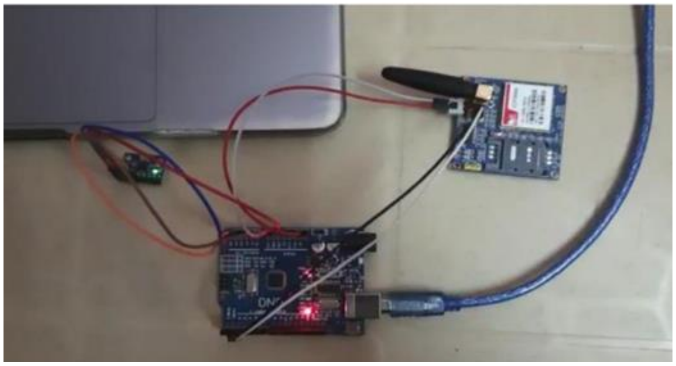

Fig2: Fall Detection hardware

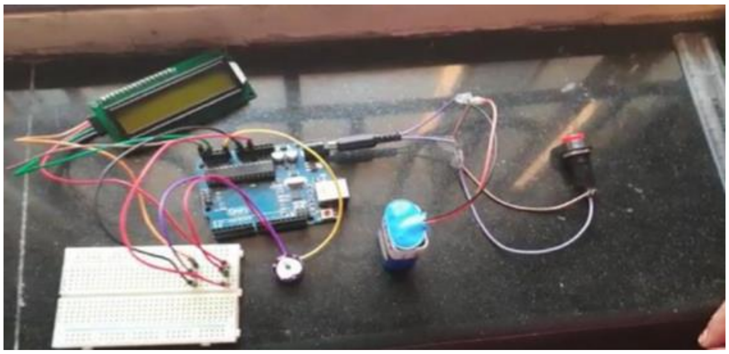

Fig3: Pulse detector hardware

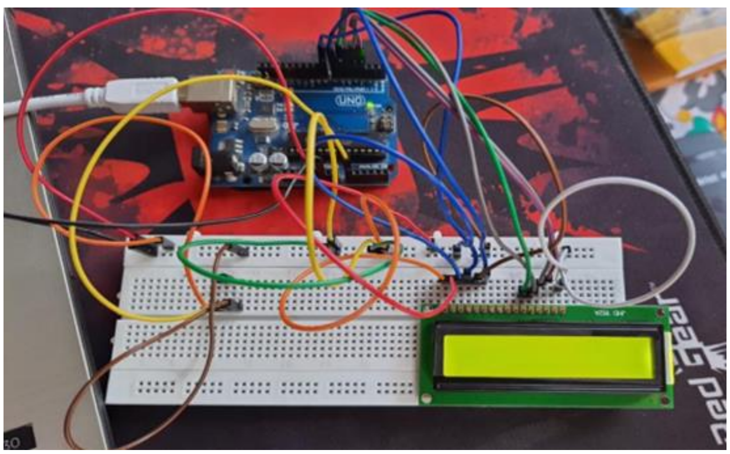

Fig 4: Fever detector hardware

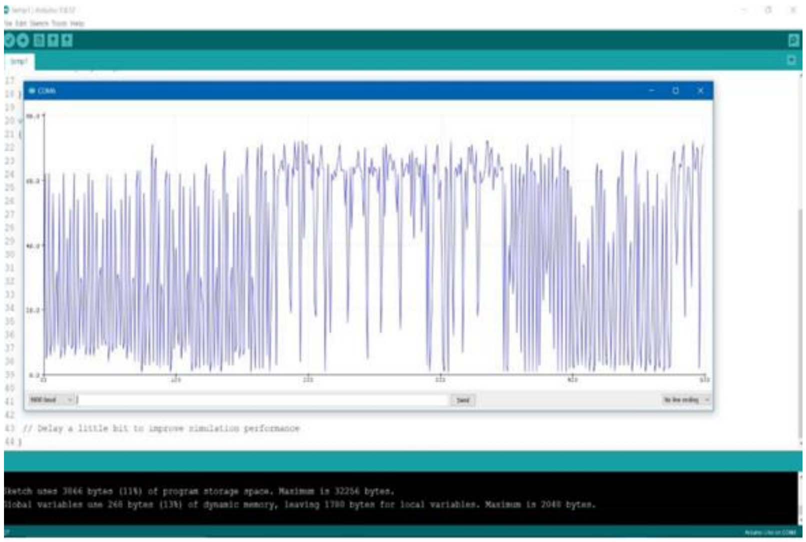

Fig 5: Body Temperature Graph

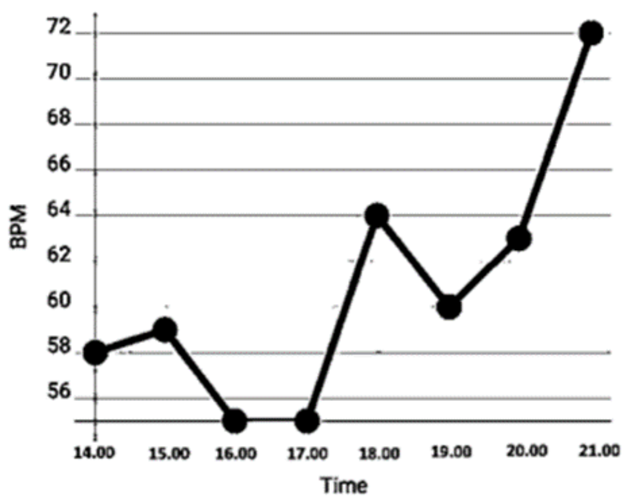

Fig 6: Heartbeat graph

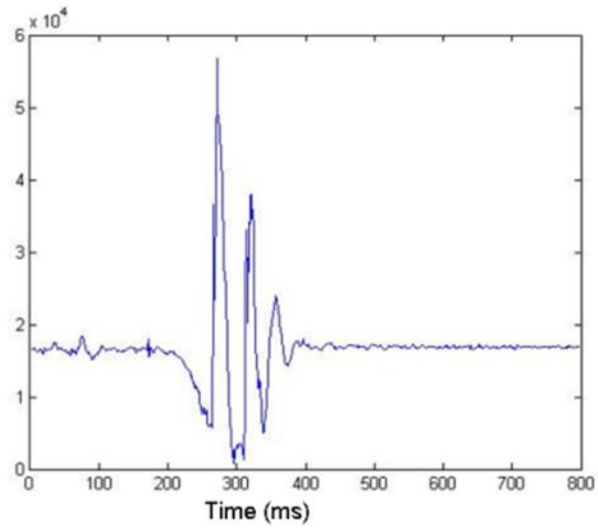

Fig 7: Fall acceleration graph

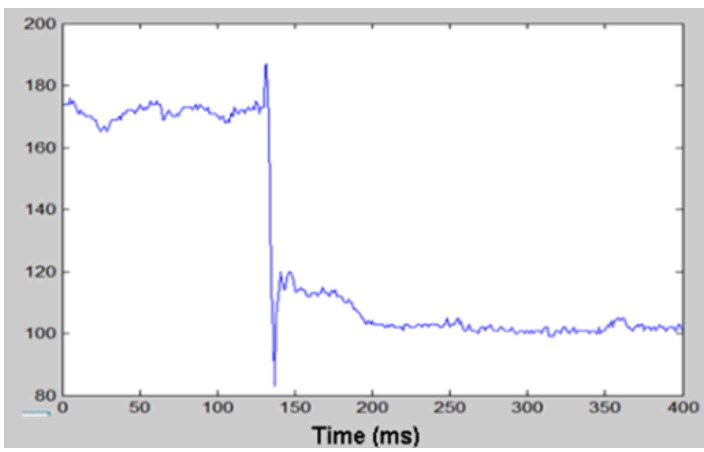

Fig 8: Position graph

Conclusions –

Fall-protection equipment, when used appropriately and regularly, has the ability to prevent many injuries and fatalities caused by falling. Additional features of the equipment include fever detection and heartbeat detection. Machine learning methods and datasets can be used to improve the device's precision and accuracy. This device has the potential to save countless lives and improve people's lives.

One of the major limitations encountered with this study is that the fall-detection algorithm was tested on people within the age category of 20-30 years. Also, the falls were simulated on purpose rather than being a natural fall. Further testing is required with people of above 60 years to make the system more accurate

Future prospects –

This project aims at sensing the temperature, fall and pulse rate of elderly people. This could be extended to sick patients of all age groups making it easier for the hospital staff and their relatives to take care of them without having to take their vitals all the time. It ensures their safety both from external stimuli and internal reactions. The following future directions can be looked at:

1. Energy Efficiency: In a more realistic setting, a wearable-based technology can be used. These sensors, however, are small and have a limited lifetime and processing power. As a result, energy efficiency algorithms are necessary to improve the system's feasibility. Another potential way to increase the system's significance is to use an energy collector. Fog computing, also known as edge computing, is a promising way to reduce the impact of resource-intensive machine learning methods. The compute load at the sensors can be reduced by processing at the edge. As a result, it's ideal for creating a fall detection software. Edge computing, on the other hand, causes delays that make it unsuitable for fall prevention applications.

2. Datasets: For their experiments, the majority of research developed a dataset. The dataset, on the other hand, was mostly tiny and composed of healthy people. The accuracy of categorization is improved by using large datasets. As a result, enormous datasets, mostly Internet of Things Project Final Review Date – 1/12/2021 comprised of geriatric data, are required. There should be more genuine datasets developed, as present datasets include samples from persons under the age of 40, who are physically different from people over the age of 60. Custom data combined with public datasets can produce more accurate results. The Generative Adversarial Network (GAN) is another option for improving datasets.

3. Context Awareness: Another fascinating future direction is context awareness. Typically, fall prevention software is based on gait. Individual gaits, on the other hand, differ from one surface to the next. On a regular floor, for example, a person's gait would be different than on sand. As a result, a context-aware system that integrates this challenge and reduces false alerts is required.

4. Sensor Fusion: Sensor fusion is based on the idea of merging data from numerous sensors in order to make a conclusion. It aids in the reduction of data uncertainties. As a result, sensor fusion could be a promising new avenue for fall detection and prevention systems in the future.

5. Wearable Design: Users will typically use the sensor-based solution for extended periods of time. A system can sometimes have more than one sensor and electrodes. As a result, creating a user-friendly system is an intriguing future direction.

References –

[1] Harrou, Fouzi & Zerrouki, Nabil & Sun, Ying & Houacine, Amrane,” Vision-based fall detection system for improving safety of elderly people”, *IEEE Instrumentation & Measurement Magazine, 20. 49-55. 10.1109/MIM.2017.8121952*.

[2] Vallabh, Pranesh & Malekian, Reza & Ye, Ning & Capeska Bogatinoska, Dijana,” Fall Detection Using Machine Learning Algorithms”, 2016 *24th International Conference on Software, Telecommunications and Computer Networks (SoftCOM).*

[3] Litvak, Dima, Yaniv Zigel and I. Gannot. “Fall detection of elderly through floor vibrations and sound.” *30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (2008): 4632-4635.*

[4] Young-Hoon Nho, Jong Gwan Lim, Dae-Eon Kim, Dong-Soo Kwon, “User-adaptive Fall Detection for Patients Using Wristband*”, IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2018.*

[5] Rihana, S. and Mondalak, J.,” Wearable Fall Detection System.*3rd Middle East Conference on Biomedical Engineering (MECBME) 2017.*

[6] *The design and development of a production prototype Balance Belt* by C.Wall, III, N. D. Lyford, K. H. Sienko, M. D. Balkwill, Member, *IEEE.*

[7] *In Accelerometer-Based Fall Detection for Smart* by Bruno Aguiar , Tiago Rocha, et al.

[8] L. G. Jaimes, Y. De La Hoz, C. Eggert, and I. J. Vergara-Laurens, “Pat: A power-aware decision tree algorithm for mobile activity recognition,” in *2021 13th IEEE Annual Consumer Communications & Networking Conference (CCNC), pp. 54–59, IEEE, 2021*.

[9] L. G. Jaimes and I. J. Vergara-Laurens, “*Corredor, a mobile humancentric sensing system for activity recognition,” 2020.*

[10] L. G. Jaimes, T. Murray, and A. Raij, “Increasing trust in personal informatics tools,” in *International Conference of Design, User Experience, and Usability, pp. 520–529, Springer, 2019.*

[11] L. Valcourt, Y. De La Hoz, and M. Labrador, “Smartphone-based human fall detection system,” *IEEE Latin America Transactions, vol. 14, no. 2, pp. 1011–1017, 2016*.

[12] M. Kangas, A. Konttila, P. Lindgren, I. Winblad, and T. Jams ¨ a, “Com- ¨ parison of low-complexity fall detection algorithms for body attached accelerometers,” *Gait & posture, vol. 28, no. 2, pp. 285–291, 2008.*

[13] G.-C. Chen, C.-N. Huang, C.-Y. Chiang, C.-J. Hsieh, and C.-T. Chan, “A reliable fall detection system based on wearable sensor and signal magnitude area for elderly residents,” in *International Conference on Smart Homes and Health Telematics, pp. 267–270, Springer, 2014*.

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- Optimal Number of Cooperators in the Cooperative Spectrum Sensing Schemes Sriharipriya K C and K. Baskaran *2018 | Birkhauser Boston*